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Use of Dynamic Neural Networks for Modeling Nonlinear Objects with Significant Nonlinearity

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***Abstract*—The work is devoted to the problem of nonlinear modeling of objects based on dynamic neural networks. The aim of the work is to improve the accuracy of modeling dynamic objects with significant nonlinearities using neural network models, and identify the scope of their effective application. This aim is achieved by applying the dynamic nonlinear models in the form of time delay neural networks. The scientific novelty of the work lies in the determination of the dependences between the accuracy of suggested models and the types of model input signals, as well as the amplitudes of model input signals. Practical usefulness of the research lies in the determination of the area of effective use of suggested models of dynamic objects with significantly nonlinear features, such us saturation. Significance of the obtained results: the application of the proposed models for identification dynamic objects with significantly nonlinear characteristics allows to improve the accuracy of the modelling process in comparison with models based on deterministic identification methods, such as integro-power series based on multidimensional weight functions.**

***Index Terms*—Identification, nonlinear dynamic objects, significant nonlinearities, time delay neural networks.**

I. Introduction

TODAY, as a result of the development of technology and science, practical applications increasingly consider dynamic control objects characterized by significantly nonlinear properties. Due to these characteristics, objects can function in more complex modes than objects with characteristics in the form of linear or insignificant nonlinear functions [1]. A non-significantly nonlinear function should be understood as the case when the nonlinear function and its 1st and 2nd order derivatives are continuous over the entire range of input signal changes. Nonlinear links that do not satisfy this condition are considered to be significant nonlinearities [2].

For successful interaction with such objects (solving control, management, and diagnostic tasks), it is first of all necessary to ensure their adequate mathematical support and effective modeling tools. However, the presence of significantly nonlinear characteristics makes the use of existing analytical methods ineffective. Such models don't reflect the dynamic and nonlinear properties of a real object, so they cannot provide high identification accuracy [2]. An up-to-date approach to modeling nonlinear dynamic objects is the artificial neural network apparatus [3-7].

The aim of the work is to improve the accuracy of modeling dynamic objects with significant nonlinearities using neural network models, and identify the scope of their effective application.

This goal can be achieved by examining the existing architectures of neural networks for modeling nonlinear dynamic objects and identifying their advantages, disadvantages and determining the areas for their effective use. The following tasks are considered within the framework of this work:

1. Study of modeling accuracy of nonlinear objects with smooth nonlinearity.
2. Study of modeling accuracy of nonlinear objects with piecewise linear nonlinearity.

II. Relevant works

Today several methods for modeling nonlinear dynamic objects based on artificial neural networks are known [8, 9]. There are Dynamic Neurospatial Mapping (Dynamic Neuro-SM) [10, 11], Time-Delay Neural Networks (TDNN) [12, 13] and Wiener-type Dynamic Neural Networks (Wiener-type DNN) [14-16].

Dynamic Neuro-SM type models are improvements over the well-known Static Neuro-SM models [10, 11], which aim to map a given approximate model of an object to an exact model. Dynamic Neuro-SM models use neural networks to transform an existing (rough) model into a desired (exact) model using machine learning approach [10]. Such models provide improved accuracy compared to Static Neurospatial Mapping models, but assume some a priori information about the laws of functioning of the object under study [11].

Wiener-type DNN is based on the principle of building a nonlinear dynamic Winner model. This model consists of two parts arranged in series: linear dynamic and nonlinear static models [14, 15]. In this case, the dynamic properties of the object are reproduced by a linear model, and the non-linear properties are reproduced in a static non-linear model. In Wiener-type DNN static non-linear model is implemented as an artificial neural network [14-16]. This structure can significantly increase the reliability of the dynamic neural model, but has a complex (hybrid) structure, which imposes additional requirements on the network learning algorithms and narrows the scope of the model.

Among the considered variants of models TDNN are the most general structures consisting of several layers with direct connection (direct signal propagation) [12]. Such models are capable of learning from the input-output experimental data of nonlinear dynamic objects [12, 13]. These models have good convergence, which is an advantage over the models based on Dynamic Neuro-SM and Wiener-type DNN models, mentioned above. So, using of TDNN for modeling dynamic objects with highly nonlinear characteristics provides unique advantages over other models.

III. Time-Delayed Neural Nets

TDNN models are an effective tool for modeling non-linear dynamic objects with continuous characteristics. The most commonly used structure of TDNN consists of three layers: input, hidden and output.

There are many structures of neural networks: with several hidden layers, different activation functions and topologies. However, using this models gives more complex expression for model output data. This is a significant disadvantage in comparison with three-layer neural networks for modeling nonlinear dynamic objects.

The input layer of TDNN includes M neurons, where M is a length of the object's model memory. The number of neurons M is chosen in such a way as to best reflect the dynamic properties of the object [17].

The number of neurons K is chosen in such a way as to best fit the training set.). It receive input data $\mathbf{x}_n(t)=[x(t_n), x(t_{n-1}), \dots , x(t_{n-M-1})]$, $t_n=n\Delta t$, $n=1, 2, \dots$ The hidden layer includes K neurons with a nonlinear activation function. The number of neurons K is chosen in such a way as to best reflect the nonlinear properties of the object.

The output layer includes 1 neuron with a linear activation function. The signal $y_n(t)$ on the output layer at the time t_n depends as on the value of input signal $\mathbf{x}_n(t)$ at the current moment t_n, as on input data $x(t_n), \dots , x(t_{n-M-1})$ at the times $t_n, \dots , t_{n-M-1}$. So, the output data $y_n(t)$ of TDNN model are determined by the expression:

$$y(t_n) = b_0 + s_0 \sum_{i=1}^{K} w_i\, S_i \left(b_i + \sum_{j=1}^{M} w_{i,j} x(t_{n-j}) \right), \qquad (1)$$

where b_0, b_i – biases of the output and hidden layers neurons accordingly; S_0, S_i – activation functions of the output and input layers neurons accordingly; w_i, $w_{i,j}$ – weighing coefficients of the output and hidden layers neurons accordingly.

The activation function can be expressed as a polynomial of degree p. Then the output data $y_n(t)$ of TDNN model are determined by the expression [17, 18]:

$$y(t_n) = b_0 + s_0 \sum_{i=1}^{K} w_i\, S_i \left(b_i + \sum_{j=1}^{M} w_{i,j} x(t_{n-j}) \right)^p . \qquad (2)$$

Fig. 1 shows a three-layer TDNN with M inputs, a hidden layer with J neurons, and one output neuron.

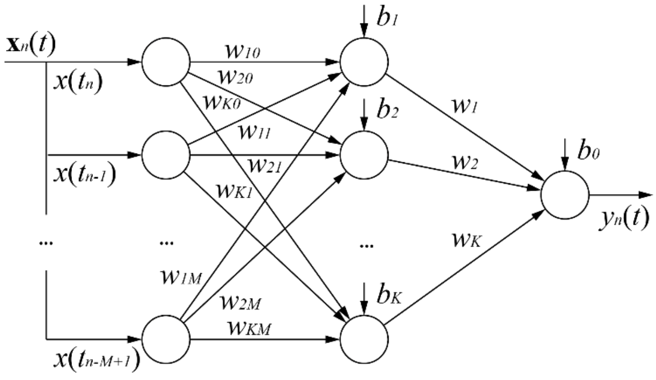


Fig. 1. Three-layer TDNN with M inputs and K hidden neurons

TDNN network can quickly learns dynamic behavior taking into account high-order nonlinear characteristics [18, 19] if they are trained on the data of input-output experiments.

IV. Experimental Setup

The effectiveness of the TDNN models is studied on the example of the test object. Test object simulation model with a first-order dynamic block and nonlinear block in feedback [20] is shown on Fig. 2.

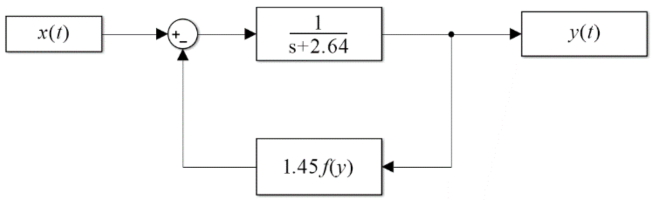


Fig. 2. Block diagram of the test nonlinear dynamical object

The polynomial function and function with saturation are used as a nonlinear feature $f(y)$ in feedback block of the simulation model.

To research the accuracy of modeling dynamic objects with significant nonlinearities using neural network models, and identify the scope of their effective application it is necessary to create training and test datasets from input and output signals.

To form a training and test dataset the test signals $x(t)$ in the form of impulse, step, linear and harmonic functions with different amplitudes a are applied to the input of the simulation model. As a result, a set of output reactions $y(t)$ and sequential segments $\mathbf{x}_n(t)$ of input signal $x(t)$, shifted by one value Δt for each type of nonlinear feature $f(y)$ forms a training and test dataset.

To model objects with different types of nonlinearity, it is necessary to train TDNN on each of the generated datasets [21-23].

To create a neural network, the Keras (keras.io) software tool is used. It is one of the key Python libraries for efficiently organizing APIs when modeling neural networks of any complexity. The library is most effective when building small networks with a sequential structure, where layers follow each other and one input and one output layer. Although it is possible to model more complex neural network structures with multiple inputs and outputs.

To build feedforward networks with Keras we can use an any number of sequential layers of the predefined types: Input, Dense and Activation. The library has a ready-made set of loss functions and optimization algorithms that allow us to quickly train the model and avoid local minima whenever possible.

As a result, a three-layer neural network was created and trained. The input signal $x(t)$ is fed to the M neurons of the input layer. The hidden layer consists of K neurons. The output layer consists of one neuron with a linear activation function. The block diagram of the TDNN is shown on Fig. 3. In this figure, the value *None* in the data dimension vector means a variable number of rows in the dataset.

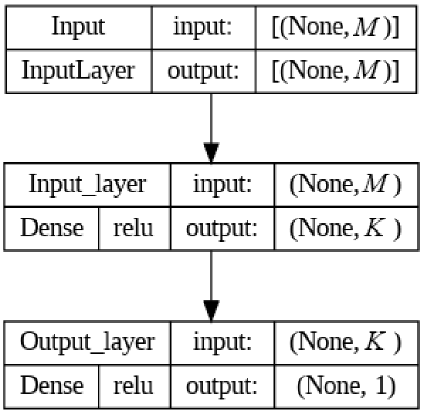


Fig. 3. Structure diagram of the TDNN with M inputs and K hidden neurons

To determine the best values of M and K in the given structure of TDNN a number of neural networks with different numbers of neurons in the input M and hidden K layers are constructed [24]. The result of experiment in the form of the loss as a function of the neurons number in the input M and hidden K layers is presented in Fig. 4.

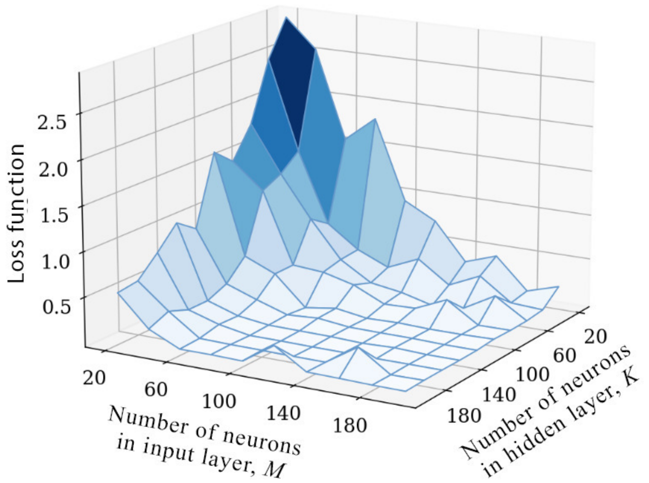


Fig. 4. Loss as a function of the neurons number in the input M and hidden K layers

The result experiment as a dependence of the learning time (epoch) on the neurons number in the input M and hidden K layers are presented in Fig. 5. As a result of TDNN structure experiment, the values M=15 and K=50 were accepted for the number of neurons in the input and hidden layers of the TDNN respectively. The resulting TDNN was used to research the accuracy of models for dynamic objects with significant nonlinearities [25, 26].

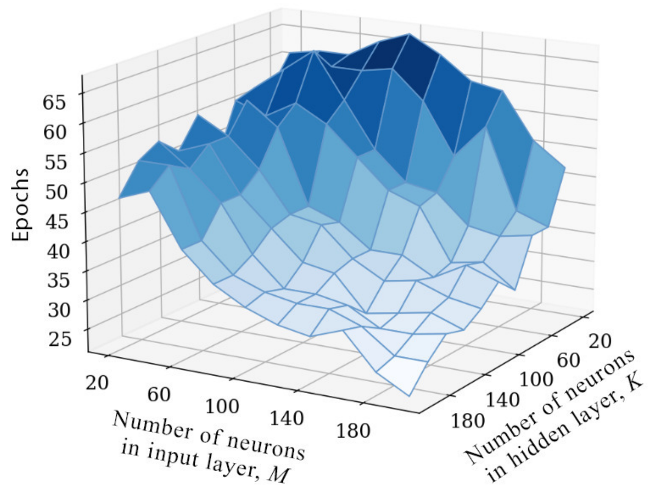


Fig. 5. Epochs as a function of the neurons number in the input M and hidden K layers

For the study the accuracy of modeling dynamic objects with significant nonlinearities using neural network models, and identify the scope of their effective application, two experiments were organized and executed:

1. Study of the scalability of the model to various input signals.
2. Study of extrapolation properties of the model.

The results of both experiments are compared with the results of simulation and identification using deterministic identification methods, such as integro-power series based on multidimensional weight functions.

A. Study of the scalability of the model to various input signals.

The training dataset includes impulse signals $x(t) = a\delta(t)$ various amplitude ($a \in (0, 1]$) at the input of the object and its response $y(t)$ on the output. The test dataset includes step $x(t)=a\Theta(t)$, linear $x(t)=at$ and harmonic $x(t)=a\sin(t)$ signals various amplitude ($a \in (0, 1]$) at the input of the object and its response $y(t)$ on the output.

A TDNN model builds on the data of the training dataset. The accuracy of the model is tested on the data of the test dataset (signals that are not part of the training sample).

The experiment executes for objects with nonlinear feature $f(y)$ in feedback block in the form of smooth (polynomial) as well as saturation function. Based on the results of the experiment, we make a conclusion about the area of effective use of TDNN models. The model output $y_n(t)$ is compared with the model output $y(t)$ obtained by the simulation and the model output $y_v(t)$ based on deterministic identification methods, such as integro-power series based on multidimensional weight functions [27-29].

Fig. 6 shows a comparison of the output signals $y_n(t)$, $y_v(t)$ and $y(t)$, obtained as a result of the input signal $x(t)=a\delta(t)$ on the TDNN model, integro-power model and simulation the nonlinear dynamical object (fig. 2) for nonlinear feature $f(y)$ in feedback block in the form of polynomial function.

This experiment shows comparable modeling accuracy using TDNN and integro-power models under the action of input signals $x(t) = a\delta(t)$ various amplitude ($a \in (0, 1]$).

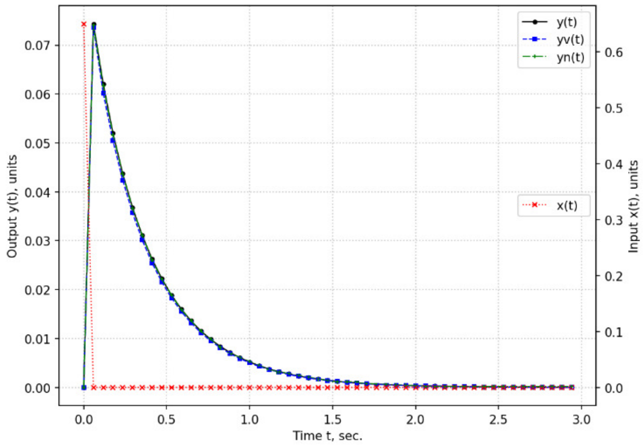


Fig. 6. Comparison of the output signals $y_n(t)$, $y_v(t)$ and $y(t)$, obtained as a result of the input signal $x(t)=a\delta(t)$ (a=0.65) on the TDNN model, integro-power model and simulation the nonlinear dynamical object respectively for nonlinear feature $f(y)$ in feedback block in the form of polynomial function

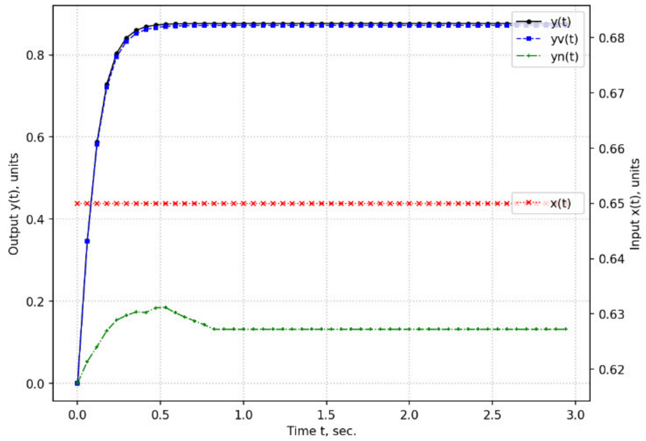
This figure shows a comparison of the output signals $y_n(t)$, $y_v(t)$ and $y(t)$, obtained as a result of the input signals $x(t)=a\Theta(t)$ (fig. 7a), $x(t)=at$ (fig. 7b) and $x(t)=asin(t)$ (fig. 7c) on the TDNN model, integro-power model and simulation the nonlinear dynamical object for nonlinear feature $f(y)$ in feedback block in the form of polynomial function. This experiment shows that the TDNN model is significantly inferior in accuracy to integro-power models under the action of input signals $x(t)$ various amplitude ($a \in (0, 1]$), which were not included in the training dataset.

The conclusion follows from the experiment: TDNN models are not invariant to the form of the input signal. The TDNN model can adequately reflect the properties of the dynamic object in the case of training on a sufficient amount of data. The training dataset must include input signals various amplitude of the same type as in the test dataset. This is a disadvantage of neural network models in comparison with models based on deterministic identification methods, such us integro-power series on the base of multidimensional weight functions [29, 31].

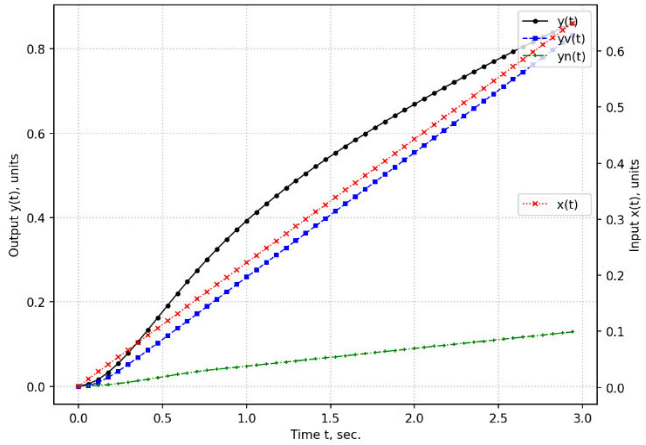
B. *Study of extrapolation properties of the model.*

The training dataset includes impulse $x(t)=a\delta(t)$, step $x(t)=a\Theta(t)$, linear $x(t)=at$ and harmonic $x(t)=asin(t)$ signals various amplitude ($a \in (0, 1]$) at the input of the object and its response $y(t)$ on the output. Simulating data are obtained for objects with nonlinear feature $f(y)$ in feedback block in the form of saturation function.The test dataset includes the same input signals with amplitude in the interval (1, 2] and responses at the output. The accuracy of the model is tested on the data of the test dataset (signals that are not part of the training sample).

The experiment executes for objects with nonlinear feature $f(y)$ in feedback block in the form of saturation function. Based on the results of the experiment, we make a conclusion about the area of effective use of TDNN models. The model output $y_n(t)$ is compared with the model output $y(t)$ obtained by the simulation and the model output $y_v(t)$ based on deterministic identification methods, such as integro-power series based on multidimensional weight functions.



a



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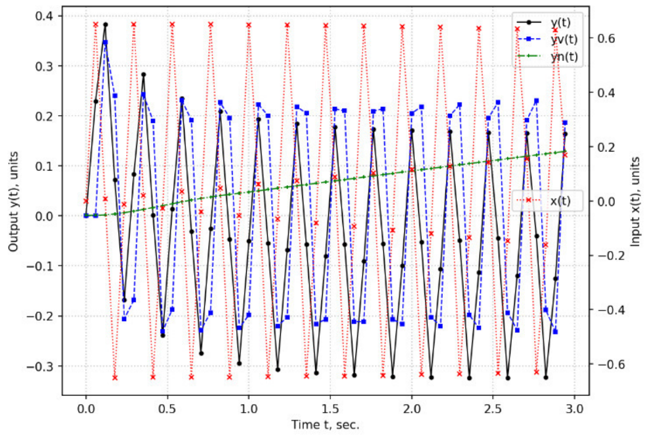


c

Fig. 7. Comparison of the output signals $y_n(t)$, $y_v(t)$ and $y(t)$, obtained as a result of the input signal $x(t)$ (a=0.65) on the TDNN model, integro-power model and simulation the nonlinear dynamical object respectively for nonlinear feature $f(y)$ in feedback block in the form of polynomial function: a – $x(t)=a\Theta(t)$; b – $x(t)=at$; c – $x(t)=a\sin(t)$; a=0.65

This figure shows a comparison of the output signals $y_n(t)$, $y_v(t)$ and $y(t)$, obtained as a result of the input signal $x(t)=a\Theta(t)$ (a=0.7) on the TDNN model, integro-power model and simulation the nonlinear dynamical object respectively for nonlinear feature $f(y)$ in feedback block in the form of saturation function.

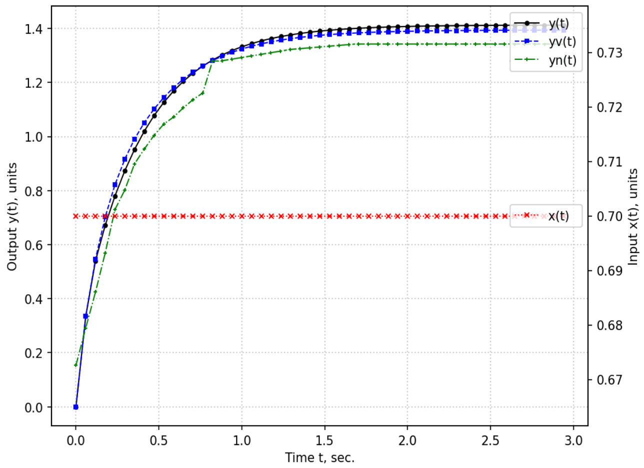


Fig. 8. Comparison of the output signals $y_n(t)$, $y_v(t)$ and $y(t)$, obtained as a result of the input signal $x(t)=a\Theta(t)$ (a=0.7) on the TDNN model, integro-power model and simulation the nonlinear dynamical object respectively for nonlinear feature $f(y)$ in feedback block in the form of saturation function

This figure shows a comparison of the output signals $y_n(t)$, $y_v(t)$ and $y(t)$, obtained as a result of the input signal $x(t)=a\Theta(t)$ (a=1.65) on the TDNN model, integro-power model and simulation the nonlinear dynamical object respectively for nonlinear feature $f(y)$ in feedback block in the form of saturation function.

This experiment shows that the integro-power model lose their accuracy in interpolation and extrapolation tasks when dealing with dynamic objects with significant nonlinear features, for example, saturation function $f(y)$. The obtained simulation results for the dynamic objects with significant nonlinear features allow to conclude that the extrapolation properties of TDNN model are far superior in accuracy to integro-power models under the action of input signals $x(t)$ various amplitude ($a \in (1, 2]$) for all types of signals present in the training dataset.

The obtained results make it possible to determine the area of effective application of TDNN models when modeling dynamic objects with significant nonlinearities.

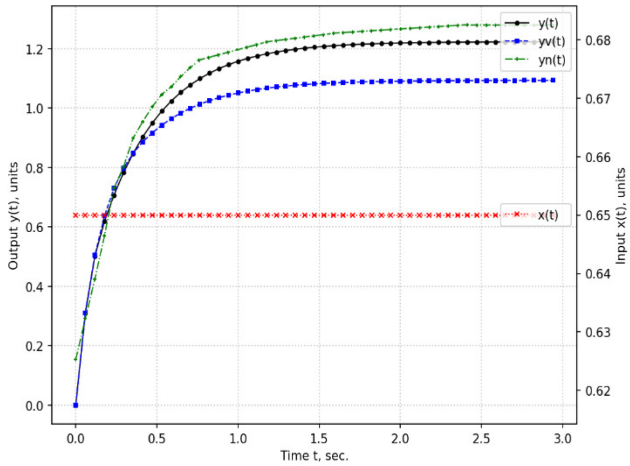
Conclusion

The results of this research are as follows.

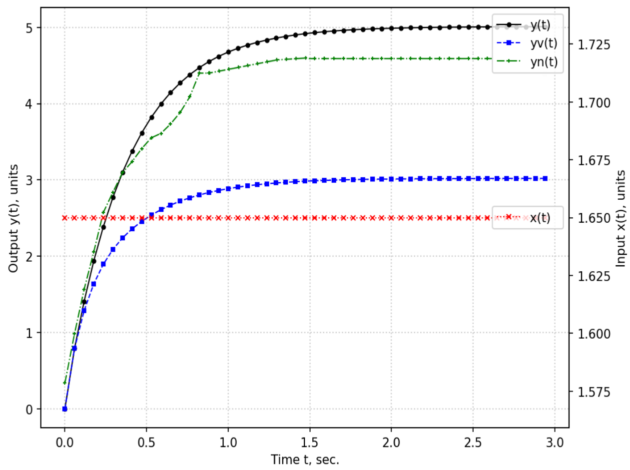
The scientific novelty of the work lies in the determination of the dependences between the accuracy of TDNN models and the types of model input signals, as well as the amplitudes of model input signals.

Practical usefulness of the research lies in the determination of the area of effective use of TDNN models – dynamic objects with significantly nonlinear features.

Significance of the obtained results: the application of the proposed models for identification dynamic objects with significantly nonlinear characteristics allows to improve the accuracy of the modelling process in comparison with models based on deterministic identification methods, such as integro-power series based on multidimensional weight functions.



a



b

Fig. 9. Comparison of the output signals $y_n(t)$, $y_v(t)$ and $y(t)$, obtained as a result of the input signal $x(t)=a\Theta(t)$ on the TDNN model, integro-power model and simulation the nonlinear dynamical object respectively for nonlinear feature $f(y)$ in feedback block in the form of saturation function: a – interpolation task (a=0.65); b – extrapolation task (a=1.65)

TDNN models are not invariant to the form of the input signal. The TDNN model can adequately reflect the properties of the dynamic object in the case of training on a sufficient amount of data. The training dataset must include input signals various amplitude of the same type as in the test dataset. This is a disadvantage of neural network models in comparison with models based on deterministic identification methods, such as integro-power series on the base of multidimensional weight functions.

The interpolation and extrapolation properties of TDNN model are far superior in accuracy to integro-power models under the action of input signals $x(t)$ various amplitude ($a \in (1, 2]$) for all types of signals present in the training dataset for dynamic objects with significant nonlinearities.

The obtained results make it possible to determine the area of effective application of TDNN models when modeling dynamic objects with significant nonlinearities.

The proposed models verified using the data of the test dynamical objects with significant nonlinearities such as polynomial and saturation functions.

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